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ORIGINAL RESEARCH

A multi-objectives based technique for optimized routing in opportunistic networks

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Abstract In the design of routing protocols for opportunistic networks (OppNets), the node's context information such as number of encounters to destination (EN), distance to destination (DI), delivery probability (PR), to name a few, is used as routing decision patterns when selecting the best next hop candidate to forward the data packets to their destination. Most routing protocols thus far proposed for OppNets have considered either of these patterns or a combination of few of them as design objectives in their next hop selection processes. But none of these work have ever addressed their optimization for the same. In this regard, this paper proposes a novel multi-objectives based technique for optimized routing (MOTOR) in OppNets. This technique involves the use of a weighted function to decide on the next hop selection of a node based on a combination of objectives, namely, maximizing the number of encounters (EN), maximizing the delivery probability (PR), and minimizing the distance to destination (DI). A non-dominated set of solutions is proposed using a Naive and Slow algorithm for forwarding the data packets towards their destination. Simulation results are provided to assess the performance of the MOTOR scheme when the next hop selection process relies on a single objective (EN, PR, or DI), double objectives (EN–DI, EN–PR, or DI–PR), and triple objectives (EN–DI–PR). It is shown that the performance of the proposed routing scheme under the triple objectives option is better than that obtained under all the three double objectives in terms of delivery probability, average latency and number of messages dropped. For instance there is 6%, 41.84% and 29.26% increase in delivery probability, average latency and number of messages dropped respectively in triple objectives with respect to the double objectives DI–PR.

Keywords Opportunistic networks (OppNets) · Opportunistic Network Environment (ONE) simulator · multi-objectives · Prophet · EDR protocol · PRoWait · Delay tolerant network (DTN)

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1 Introduction

In OppNets (Palazzo et al. 2008), constraints such as link instability, node mobility, short communication range, intermittent connectivity, frequent partitioning of the network, to name a few, constitute a major burden when attempting to establish an end-to-end path for routing in such networks. To address this problem, a store-carry-and-forward mechanism (Boldrini 2007) is used, which involves exploiting pairwise contact opportunities as a mean for achieving the routing of data packets from source to destination assuming that there is some form of cooperation between the nodes and no malicious activity prevails.

The routing of data packets in OppNets is a challenging task (Boldrini 2007) due to the inconsistency in connectivity and a lack of knowledge of the node's location and network topology. For this reason, designing an efficient routing protocol for OppNets requires the use all possible informative contexts such as the node's delivery probability, number of encounters to destination, distance to destination, energy consumption, past and present history, to name a few.

In principle, although combining many objectives when making the next hop selection decision may seem to lead to conflict, this paper reports on the feasibility of an optimized combination of objectives by proposing the so-called multi-objectives technique for optimized routing in OppNets (MOTOR for short). This technique relies on the design and optimization of a weighted function to determine a suitable next hop forwarder of a given node, with focus on achieving a combination of objectives, namely maximizing the number of encounters (EN), maximizing the delivery probability (PR), and minimizing the distance to destination (DI). Based on this technique, a non-dominated set of solutions is derived using a Naive and Slow algorithm for forwarding the data packets towards their destination.

The rest of the paper is organized as follows. In Sect. 2, representative routing protocols for OppNets are overviewed. In Sect. 3, the proposed multi-objectives technique (MOTOR) is described in-depth. In Sect. 4, simulation results are presented. Section 5 concludes the paper.

2 Related work

In the literature, a number of context and dissemination based routing protocols for OppNets have been proposed. Representative ones are discussed as follows.

Lindgren et al. (2003) proposed the Prophet protocol in which before transferring a message, each node calculates a probability metric so called delivery predictability with respect to its corresponding destination. The parameters that are involved in this calculation include the history of visits of a node to certain locations and the history of its encounters with other nodes. The following facts also prevails: (a) whenever two nodes meet, their delivery predictability are updated according to the equation (Lindgren et al. 2003):

$$P_A(B)_{new} = P_A(B)_{old} + (1 - P_A(B)_{old}) * P_{init} \tag{1}$$

where $P_{init} \in [0, 1]$ is a scaling factor set at a rate at which the predictability increases when nodes get in contact with each other; (b) if a pair of nodes do not find each other for a certain amount of time, they are less likely to be considered as good forwarders of messages and their delivery predictability values must age. It should be noted that the delivery predictability value of a node is reduced according to the following equation (Lindgren et al. 2003):

$$P_A(B)_{new} = P_A(B)_{old} \times \gamma^K \tag{2}$$

where $\gamma \in [0, 1]$ is the aging constant and K is the number of time units since the last decay; (c) if node A frequently meets node B, which itself frequently meets node C, then node C is likely to be a good forwarder of the messages directed to node A, i.e. the following equation prevails (Lindgren et al. 2003):

$$P_A(C)_{new} = P_A(C)_{old} + (1 - P_A(C)_{old}) \times P_A(B) \times P_B(C) \times \beta \tag{3}$$

where $\beta \in [0, 1]$ is a scaling constant factor used to control the impact of the transitivity property over the delivery probability; (d) a message is forwarded to nodes whose delivery predictability with respect to the destination is higher; and (e) the first node does not delete the message after transmitting it as long as there is sufficient buffer space available with it. It is worth mentioning that the Prophet protocol does not consider any other parameters such as number of encounters of a node, distance to destination, to name a few, when determining the delivery predictability of a node.

Dhurandher et al. (2016) proposed a routing scheme for OppNets called Encounter and Distance-based Routing protocol (EDR) which is based on the context information of nodes. Initially, the encounter values (resp. of the Euclidean distance) of each pair of nodes in the network are calculated dynamically. For the selection of next hop of a node, EDR calculates the so-called best forwarding parameter $\gamma = \alpha/\beta$, where

$$\alpha = Node\ Encounter/SumEncounter$$

$$\beta = Node\ Distance/SumDistance.$$

Node Encounter is the encounter value of a node, defined as the number of times that it has opportunistically encounter another node, *SumEncounter* is the sum of the encounters of all the neighboring nodes with the destination, *Node Distance* is the Euclidean distance of a node with the destination, and *SumDistance* is the sum of the Euclidean distances of all the neighboring nodes with the destination. The messages are then forwarded to only those neighbouring nodes whose γ values are greater than or equal to a prescribed threshold T. It should be noted that EDR does not perform well in terms of message delivery probability.

Dhurandher et al. (2013a) proposed the HBPR protocol for OppNets which is based on the history of nodes. In this scheme, the selection of the next hop to forward the message is determined based on three parameters, namely, the time of meeting of two nodes, the time interval of the meeting, and the direction of the node movement with respect to source and destination. Using these parameters, the protocol is implemented in three phases: (1) home location identification—where all nodes' locations are initially identified, (2) message generation and home location update—where selected messages are generated and the destination IDs for each of these messages are recorded, and the nodes locations are updated/maintained, and (3) next hop selection—which relies on the use of a utility metric involving three parameters: (a) stability of node movement, (b) prediction of the future movement of a node, and (c) perpendicular distance of the neighbouring node from the line of sight of the source-destination.

Dhurandher et al. (2014) proposed an energy efficient routing protocol for OppNets (called GAER), which uses a genetic algorithm to send the message copies from source to destination. In this scheme, the node's personal information table, as well as the information on the home locations of a group of nodes with whom it has interact, are used in the genetic algorithm to perform the next hop selection. Typically, a set of random chromosomes are initialized, and a fitness function is implemented, which help determining the suitability of a node as best forwarder to carry the message to the destination.

3 Multi-objectives technique for optimized routing scheme

3.1 Notations and definitions

In this work, the following notations are considered

- W_1: Weight for encounter.
- W_2: Weight for distance.
- W_3: Weight for probability.
- T_{EN}: Threshold value for encounter.
- T_{DI}: Threshold value for distance.
- T_{PR}: Threshold value for probability.
- T_{EN-DI}: Threshold value for encounter and distance.
- T_{EN-PR}: Threshold value for encounter and probability.
- T_{DI-PR}: Threshold value for distance and probability.
- $T_{EN-DI-PR}$: Threshold value for encounter, distance and probability.
- $EN_{Hashmap}$: Selected set for encounter objective.
- $DI_{Hashmap}$: Selected set for distance objective.
- $PR_{Hashmap}$: Selected set for probability objective.
- *Hashmap*: Selected set.
- *Hashmap**: Non-dominated selected set.
- *N*: Number of nodes in the network.
- *X*: Number of objectives.
- *SPM*: Shortage path map based model (Keranen and Ott 2007).
- *MGI*: Message generation interval.

3.2 Motivation

Most of the routing protocols designed so far for OppNets (Dhurandher et al. 2015a, b, 2016) consider the contexts such as the node's delivery probability, number of encounters to destination, past and present history information to establish a strategy that any node should follow to select a suitable next hop, i.e. a node capable of participating in forwarding the message towards the destination. In most of the routing protocols for OppNets, the design of such strategy has been formulated by focusing on either a single objective or multiple objectives. For instance, some of the protocols such as the ones discussed in Dhurandher et al. (2015a), where the next hop selection process relies on achieving the best possible delivery probability as objective; the protocol in Dhurandher et al. (2016) focuses on achieving a double objectives, that of maximizing the number of encounters while minimizing the distance to destination; the routing scheme proposed in Dhurandher et al. (2013a) focuses on achieving less energy consumption while exploiting the history of nodes, but none of the works address about these objective being optimized using Multi-Objectives Optimization for routing a message. This has motivated the authors to design and propose the MOTOR protocol.

3.3 System model

We consider an OppNet environment composed of *N* mobile nodes, which are assumed to be cooperative with each other and which have sufficient energy to participate in the transmission of messages. It is also assumed that the nodes have sufficient buffer to store their context information and they do not behave maliciously. In OppNets, it has been established (Pelusi et al. 2006) that the various context information of a node such as node's number of encounters with destination, distance to destination, delivery probability, energy, history, to name a few, can be used as parameters to decide on the next hop selection of a given node.

3.4 Considered routing decision objectives

The technique proposed in this paper considers the node's encounter (EN), distance to destination (DI), and delivery probability (PR) as routing decision objectives, where the encounter values EN of a node are calculated dynamically when pairwise contact opportunities of nodes arise. More precisely,

$$EN = \frac{e_{i,j}}{\Sigma_{i=1}^{n} e_{i,j}} \tag{4}$$

where $e_{i,j}$ is the encounter value of node i with respect to the destination j and $\Sigma_{i=1}^{n} e_{i,j}$ is the sum of encounter values of all nodes in the network. Similarly, the Euclidean distance DI between every pair of nodes in the network is calculated dynamically as

$$DI = \frac{d_{i,j}}{\Sigma_{i=1}^{n} d_{i,j}} \tag{5}$$

where $d_{i,j}$ is the distance of a node i with respect to the destination j and $\Sigma_{i=1}^{n} d_{i,j}$ is the sum of distances of all nodes to destination. Now, the delivery probability of a node in the network is calculated as

$$PR = \frac{p_{i,j}}{\Sigma_{i=1}^{n} p_{i,j}} \tag{6}$$

where $p_{i,j}$ is the delivery probability of a node i with respect to the destination j obtained from Eqs. (1), (2) and (3), and $\Sigma_{i=1}^{n} p_{i,j}$ is the sum of all the node's probability in the network. The above calculated values for each parameter are stored in Table 1.

3.5 Multi-objectives function

In the proposed routing scheme, the selection of the next hop for a node to route the data packet toward its destination is based on the following multi-objectives function f, designed based on the above calculated parameters EN, DI and PR:

$$f(EN, DI, PR) = W_1 f_1 + W_2 f_2 + W_3 f_3 \tag{7}$$

where $f_1 = f(EN) \propto EN$, $f_2 = f(DI) \propto \frac{1}{DI}$, and $f_3 = (PR) \propto PR$ are the functions associated with EN, DI, and PR respectively and W_1, W_2, and W_3 are their corresponding weights, with $W_1 + W_2 + W_3 = 1$. Based on this, data packets are routed according to the outcome of the following function:

$$f(EN, DI, PR) = W_1 f(EN) + W_2 f(DI) + W_3 f(PR) \tag{8}$$

A set of solutions is obtained via the following optimization problem

$$\begin{aligned} &\text{maximize/minimize}\, f_a(x), \quad a = 1, \dots, M \\ &\text{subject to } g_j(x) \ge 0 \quad j = 1, \dots, J \\ &\qquad h_k(x) = 0 \quad k = 1, \dots, K \\ &\qquad {x_i}^l \le x_i \le {x_i}^u, \quad i = 1, \dots, n \end{aligned}$$

where x is the vector of the n decision variables, ${x_i}^l$ and ${x_i}^u$ are respectively the lower and upper bound of the decision variable, J and K are the equality constraints, and there are M objective functions, $M \ge 2$. Here, $g_j(x)$ and $h_k(x)$ are the constraints functions. The derived solution set may contain non-dominated solutions or Pareto optimal sets.

Dominance The concept of dominance (Deb 2001; Coello et al. 2007) in multi-objectives optimization algorithms, is often used to determine a non-dominated set of solutions from the solution set. A solution x_i dominates another solution x_j if the following conditions are true (Coello et al. 2007):

- x_i is better than x_j for $f_k(x_j) \ge f_k(x_j) \quad \forall\, k = 1, \dots, N$
- x_i is strictly better than x_j for at least one objective $f_{\bar{k}}(x_i) \ge f_{\bar{k}}(x_j)$; and for at least one $\bar{k} \in \{1, 2, \dots, N\}$

Non-dominated set According to Deb (2001), a vector decision variable $x \in s \subset R^n$ is non-dominated with respect to s if there is no other $x' \in s$ such that $f(x') \le f(x)$.

Pareto optimal set According to Deb (2001), this is defined as a set which contains the vectors of the form $x \in F \subset R^n$ and the non-dominance set with respect to F.

Using the aforementioned multi-objectives function, a weighted multi-objectives optimization problem is defined as

$$\begin{aligned} &\text{minimize}\, f(k) = w_1 f_1(k) + w_2 f_2(k) + w_3 f_3(k) \\ &\text{Subject to} \quad 1 \le k \le n \\ &\qquad \Sigma_{i=1}^{3} W_i = 1 \end{aligned}$$

where $f_1(k) = EN$, $f_2(k) = 1/DI$, and $f_3(k) = PR$. Examples of algorithms that can be used to find the non-dominated set from a solution space are the Naive and Slow algorithm, the Continuously Update algorithm, and the Kung algorithm (Deb 2001). In this work, we have adopted the Naive and Slow algorithm due to its fast convergence compared to the other algorithms. Its pseudo-code is given in Algorithm 1.

Table 1 Calculated parameters

Simulation number	EN	DI	PR
1	E_1	D_1	P_1
2	E_2	D_2	P_2
3	E_3	D_3	P_3
4	E_4	D_4	P_4
…	…	…	…
n	E_n	D_n	P_n

Input: a solution x_i from the solution space S
Output: Non-dominated set $P^{'} = \{\phi\}$
Begin
for each solution $x_j \in S$ where $i \neq j$ **do**
  if solution $x_i \triangleright x_j$ **then**
    $P^i = P^i \cup \{x_i\}$
    $x_i = x_{i+1}$
    until $i \leq N$
  end if
end for
End

Algorithm 1: Naive and Slow algorithm for determining the non-dominated solution set.

In our proposed approach, the node's number of encounters (EN), distance to destination (DI), and delivery probability (PR), whose initial values can be calculated using Eqs. (4), (5) and (6) respectively, are considered as parameters when determining the next hop of a node. The following optimization problem is considered:

maximize *EN*
minimize *DI*
maximize *PR*
Subject to $e_{i,j} \geq T_{EN}$ $(C1)$
$d_{i,j} \leq T_{DI}$ $(C2)$
$p_{i,j} \in [0, 1]$ $(C3)$
$\frac{e_{i,j}}{d_{i,j}} > 1$ $(C4)$

where constraints $(C1)$ is meant to ensure that the encounter value of each node is less than or equal to T_{EN}, $(C2)$ is meant to ensure that the Euclidean distance of each intermediate node with respect to the destination is less than or equal to T_{DI}, $(C3)$ is used to ensure that the delivery probability of each intermediate node is in the interval [0, 1], and $(C4)$ is used to ensure that the node's number of encounters is maximized while its distance to destination is minimized.

3.6 Proposed routing protocol

Whenever a source node creates a message to be routed towards a destination node, it checks the value of the weights W_1, W_2 and W_3. Depending on these values and the targeted combination of objectives (i.e. DI–PR, EN–PR, EN–DI, or EN–DI–PR), the appropriate algorithm is invoked to decide on the selection of best next forwarder node to carry the message towards its destination. The pseudo-code of the MOTOR scheme is shown in Algorithm 2.

Inputs N, X, W_1, W_2 and W_3
Create/Receive a message to be routed to a destination
Number of objectives $= X$
Begin
if $X = 2$ **then**
  if $W_1 = 0$ **then**
    Call $f(DI, PR)$, which returns the set *Hashmap**
  end if
  if $W_2 = 0$ **then**
    Call $f(EN, PR)$, which returns the set *Hashmap**
  end if
  if $W_3 = 0$ **then**
    Call $f(EN, DI)$, which returns the set *Hashmap**
  end if
end if
if $X = 3$ **then**
  Call $f(EN, DI, PR)$, which returns the set *Hashmap**
end if
Transfer message from the source/intermediate to all the nodes in *Hashmap**
End

Algorithm 2: MOTOR $f(EN, DI, PR)$

The functions that are called within Algorithm 2 are described next.

3.6.1 Routing using the EN–DI combination of objectives

The routing procedure using the EN–DI objectives is shown in Algorithm 3.

$W_1 = 0.7$
$W_2 = 0.3$
$W_3 = 0.0$
Begin
for each message **do**
  for each node N in the network **do**
    EN $= \frac{e_{i,j}}{\Sigma_{i=1}^{n} e_{i,j}}$
    DI $= \frac{d_{i,j}}{\Sigma_{i=1}^{n} d_{i,j}}$
    $f(EN, DI, PR) = W_1 f_1 + W_2 f_2 + W_3 f_3$
    if $f(EN, DI, PR) \geq T_{EN-DI}$ **then**
      Insert the node in the solution set *Hashmap*
    end if
  end for
end for
Apply Naive and Slow algorithm to obtain the non-dominating set *Hashmap**
Return *Hashmap**
End

Algorithm 3: Encounter and Distance $f(EN, DI)$

Initially, the MOTOR scheme calculates the values of *EN* and *DI* using Eqs. (4) and (5) respectively. Based on these values, the EN–DI objectives function *f*(*EN*, *DI*) is evaluated by considering the evaluation of the function *f*(*EN*, *DI*, *PR*) using Eq. (8) with the assigned weights $W_1 = 0.7$, $W_2 = 0.3$, and $W_3 = 0$. Afterwards, the MOTOR scheme selects those nodes in the network whose *f*(*EN*, *DI*) values are greater than or equal to a prescribed threshold T_{EN-DI}; then stores this solution set in *Hashmap*. Next, the Naive and Slow algorithm is applied on the discovered solution set to obtain *Hashmap** the non-dominating set of the solution set in *Hashmap*.

Similarly, Algorithm 4 (resp. Algorithm 5) describes the routing procedure using the EN–PR objectives (i.e. with $W_2 = 0$) [resp. the DI–PR objectives (i.e. with $W_1 = 0$)].

$W_1 = 0.5$
$W_2 = 0.0$
$W_3 = 0.5$
Begin
for each message **do**
  for each node N in the network **do**
    EN $= \frac{e_{i,j}}{\Sigma_{i=1}^{n} e_{i,j}}$
    PR $= \frac{p_{i,j}}{\Sigma_{i=1}^{n} p_{i,j}}$
    $f(EN, DI, PR) = W_1 f_1 + W_2 f_2 + W_3 f_3$
    if $f(EN, DI, PR) \geq T_{EN-PR}$ **then**
      Insert the node in the solution set *Hashmap*
    end if
  end for
end for
Apply the Naive and Slow algorithm to obtain the non-dominating set *Hashmap**
Return *Hashmap**
End

Algorithm 4: Encounter and Delivery probability $f(EN, PR)$

$W_1 = 0.0$
$W_2 = 0.3$
$W_3 = 0.7$
Begin
for each message **do**
  for each node N in the network **do**
    DI $= \frac{d_{i,j}}{\Sigma_{i=1}^{n} d_{i,j}}$
    PR $= \frac{p_{i,j}}{\Sigma_{i=1}^{n} p_{i,j}}$
    $f(EN, DI, PR) = W_1 f_1 + W_2 f_2 + W_3 f_3$
    if $f(EN, DI, PR) \geq T_{DI-PR}$ **then**
      Insert the node in the solution set *Hashmap*
    end if
  end for
end for
Apply the Naive and Slow algorithm to obtain the non-dominating set *Hashmap**
Return *Hashmap**
End

Algorithm 5: Distance and Delivery probability $f(DI, PR)$

3.6.2 Routing using the EN–DI–PR combination of objectives

The routing procedure using the EN, DI, and PR objectives is described in Algorithm 6.

```
W_1 = 0.4
W_2 = 0.2
W_3 = 0.4
Begin
for each message do
    for each node N in the network do
        EN = e_{i,j} / Σ_{i=1}^{n} e_{i,j}
        DI = d_{i,j} / Σ_{i=1}^{n} d_{i,j}
        PR = p_{i,j} / Σ_{i=1}^{n} p_{i,j}
        f(EN, DI, PR) = W_1 f_1 + W_2 f_2 + W_3 f_3
        if f(EN, DI, PR) ≥ T_{EN-DI-PR} then
            Insert the node in the solution set Hashmap
        end if
    end for
end for
Apply the Naive and Slow algorithm to obtain the non dominating set Hashmap*
Return Hashmap*
End
```

Algorithm 6: Encounter, Distance and Delivery probability $f(EN, DI, PR)$

Initially, the MOTOR scheme calculates the values of EN, DI, and DI using Eqs. (4), (5), and (6) respectively. Based on these values, the objectives function *f*(*EN*, *DI*, *PR*) is evaluated using Eq. (8) with the assigned weights $W_1 = 0.4$,$W_2 = 0.2$, and $W_3 = 0.4$. Afterwards, the MOTOR scheme selects those nodes in the network whose *f*(*EN*, *DI*, *PR*) values are greater than or equal to a prescribed threshold $T_{EN-DI-PR}$; then stores this solution set in *Hashmap*. Next, the Naive and Slow algorithm is applied on the discovered solution set to obtain the non-dominating set *Hashmap** of the solution set in *Hashmap*.

4 Simulation results

In this section, the performance of the proposed MOTOR protocol is evaluated using the Opportunistic Network Environment (ONE) simulator (Keranen 2008). It is a Java based simulation environment that is capable of:

- Generating node movement using different movement models.
- Routing packets between nodes with various OppNet algorithms.
- Visualizing real time mobility and packet passing in graphical user interface.

The considered simulation parameters are given in Table 2.

First, the performance of the MOTOR scheme in terms of delivery probability is evaluated under any of the above-mentioned objectives function when the aforementioned thresholds are varied. Figure 1 shows that the maximum performance is obtained.

Second, the performance of the MOTOR scheme in terms of delivery probability, number of messages dropped, average latency, and overhead ratio respectively, is evaluated using any of the above mentioned combination of objectives (EN–DI, EN–PR, DI–PR and EN–DI–PR) under varying TTL values. The results are captured in Figs. 2, 3, 4 and 5 respectively.

In Fig. 2, it is observed that the delivery probability of EN–DI, EN–PR, DI–PR and EN–DI–PR decreases as the TTL is increased. This is due to the fact that the lifetime of each message increases with an increase in TTL, thus, more number of messages get stored in the node buffer, thereby more messages are likely to be dropped, leading to a decrease in message delivery probability. It is found that the EN–DI–PR objectives yields the highest delivery probability (i.e. 0.51038) compared to that obtained when considering all other combinations of objectives. In fact, in terms of delivery probability, the EN–DI–PR objectives is 2.85% better than the EN–PR objectives, 5.67% better than the EN–DI objectives, and 6% better than DI–PR objectives when the TTL is varied. These results might be attributed to the unpredictability of the node's direction when dealing with the next hop selection process.

In Fig. 3, it is observed that among all combination of objectives, the EN–DI–PR objectives yields the lowest number of messages dropped (i.e. 304,784) as the the TTL is increased. In fact, in terms of number of messages dropped, the EN–DI–PR objectives is 50.71% better than the EN–DI objectives, 40% better than the EN–PR objectives, and 29.76% better than DI–PR objectives when the TTL is varied.

In Fig. 4, it is observed that the average latency of EN–DI, EN–PR, DI–PR and EN–DI–PR increases as the TTL is increased. This is due to the fact that large TTL values increase the lifetime of the message to be stored in the node's buffer. It is found that the EN–DI–PR objectives yields the lowest average latency (i.e. 3305.25 s) compared to that obtained when considering all other combinations of objectives. It is also observed that the DI–PR objectives yields the highest average latency (i.e. 4688.3275 s). This is attributed to the fact that in this case, a node moving away from the destination is more likely to be selected as next forwarder of the message, leading to more time required for delivering the message to its destination. In terms of

Table 2 Simulation parameters

Parameter	Value
T_{EN}	2
T_{DI}	2
T_{PR}	2
T_{EN-DI}	2
T_{EN-PR}	2
T_{DI-PR}	2
$T_{EN-DI-PR}$	2
Simulation area	$4500 \times 3400\,m^2$
Total no. of nodes	96
Total grps of nodes	6
No. of grps of ped.	3
Nodes in each grp of ped.	30
Walking speed of ped.	0.5–1.5 km/h
Buffer size of ped.	15 Mb
No. of grps of tram	3
Nodes in each grp of tram	2
Speed of tram	6.5 km/h
Buffer size of tram	50 Mb
Bluetooth Tx speed	250 Kbps
Bluetooth Tx range	20 m
High speed interface Tx speed	10 Mbps
High speed interface Tx range	1500 m
Message TTL for each grps	100 min
MGI time	25–35 s
Message size	500 Kb^{-1} Mb
Node movement model	SPM
Simulation time	100,000 s

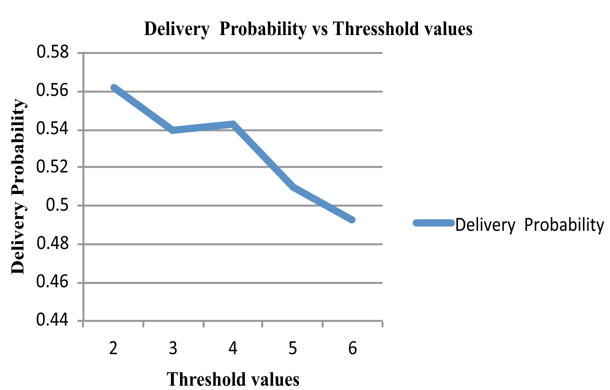

Fig. 1 Delivery probability vs threshold values

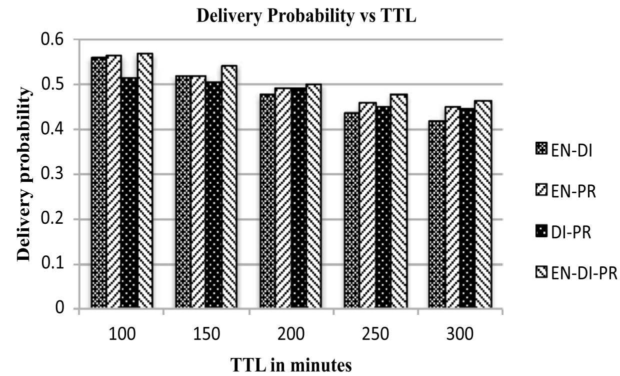

Fig. 2 Delivery probability vs. TTL

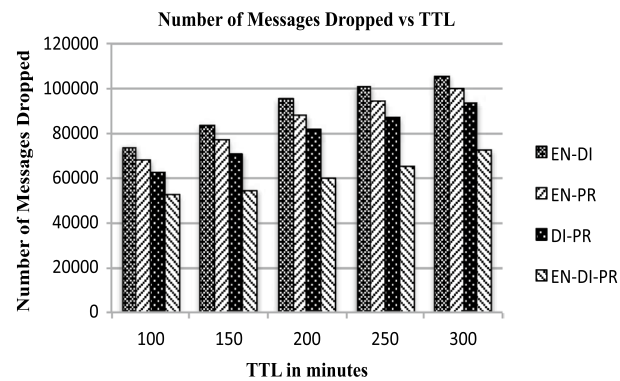

Fig. 3 Number of messages dropped vs. TTL

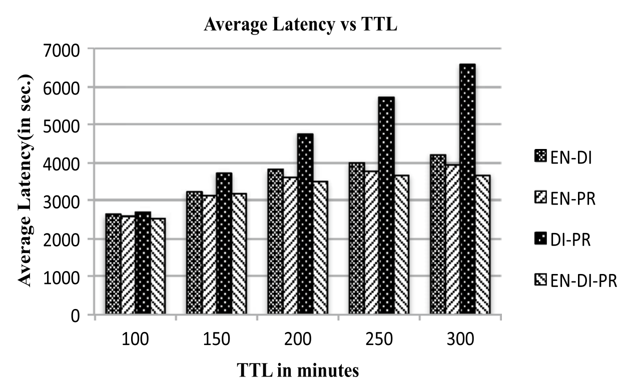

Fig. 4 Average latency (in s) vs. TTL

average latency, the EN–DI–PR objectives is 3.05% better than the EN–PR objectives, 7.92% better than the EN–DI objectives, and 41.84% better than the DI–PR objectives respectively.

In Fig. 5, it is observed that overhead ratio of EN–DI, EN–PR, DI–PR and EN–DI–PR increases as the TTL is increased. This is due to the fact that an increase in TLL value also yields an increase in the the lifetime of the message in the network. In fact, in terms of overhead ratio, the DI–PR objectives yields the lowest value compared to that obtained when considering all other combinations of objectives. This might be attributed to the fact that the number of messages generated and delivered when considering the DI–PR objective is low compared to that generated when

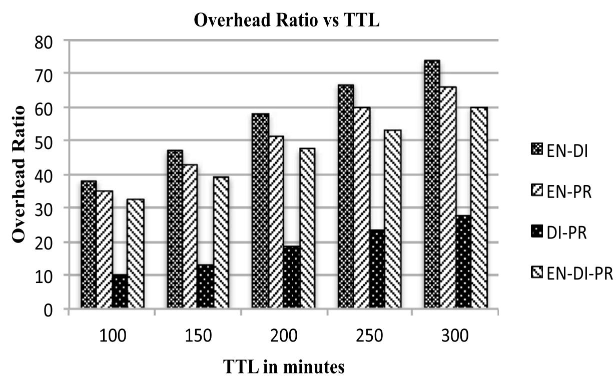

Fig. 5 Overhead ratio vs. TTL

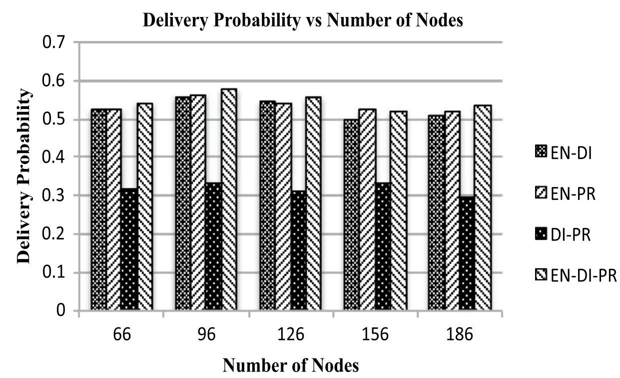

Fig. 6 Delivery probability vs. number of nodes

considering all other combination of objectives. In fact, in terms of overhead ratio, the DI–PR objectives is 3.43% better than the EN–DI–PR objectives, 4.96% better than the EN–PR objectives and 6.65% better than the EN–DI objectives. It is also observed that the EN–DI–PR objectives is 1.53% (resp. 3.22%) better than the EN–PR (resp. the EN–DI) objectives.

Third, the performance of the MOTOR scheme in terms of delivery probability, messages dropped, average latency, and overhead ratio respectively, is evaluated using any of the above mentioned combinations of objectives (EN–DI, EN–PR, DI–PR and EN–DI–PR) under varying number of nodes. The results are captured in Figs. 6, 7, 8 and 9 respectively.

In Fig. 6, it is observed that the delivery probability of EN–DI, EN–PR, DI–PR and EN–DI–PR decreases as the number of nodes is increased. This may be attributed to the fact that when the number of nodes is increased, more messages are generated in the network, which leads to more message drops, which in turn leads to a decrease in the message delivery probability. It is found that the EN–DI–PR objectives yields the highest delivery probability (i.e. 0.54586) compared to that obtained when considering all other combinations of objectives. In fact, in terms of delivery probability, the EN–DI–PR objectives is 2.145% better than the EN–PR objectives, 3.3% better than the EN–DI objectives, and 41.68% better than DI–PR objectives when the number of nodes is increased.

In Fig. 7, it is observed that among all combination of objectives, the EN–DI–PR objectives yields the lowest number of messages dropped (i.e. 99,503) as the the number of nodes is increased. In fact, in terms of number of messages dropped, the EN–DI–PR objectives is 32.39% better than the EN–DI objectives, 21.32% better than the EN–PR objectives, and 11.32% better than the DI–PR objectives when the number of nodes is increased.

In Fig. 8, it is observed that for the EN–DI, EN–PR and EN–DI–PR objectives, the average latency is decreased when the number of nodes is increased. This does not true in case of the DI–PR objectives. It is also observed that in terms of average latency, the EN–DI–PR objectives is 0.976% better than the EN–PR objectives, 3.04% better than the EN–DI objectives, and 11.35% better than the DI–PR objectives.

In Fig. 9, it is observed that the DI–PR objectives generates the lowest overhead ratio compared to that generated when considering all other combinations of objectives. In addition, the EN–DI–PR objectives is 5.6% better than the EN–PR objectives, 11.2% better than the EN–DI objectives. Furthermore, the obtained standard deviation is 61.9339 for the EN–DI–PR objectives, 14.7616 for the DI–PR objectives, 41.3623 for the EN–PR objectives and 73.134 for the EN–DI objectives.

Fourth, the performance of the MOTOR scheme in terms of delivery probability, number of messages dropped, average latency, and overhead ratio respectively, is evaluated using any of the above mentioned combinations of objectives (EN–DI, EN–PR, DI–PR and EN–DI–PR) under varying buffer size. The results are captured in Figs. 10, 11, 12 and 13 respectively.

In Fig. 10, it is observed that the delivery probability of EN–DI, EN–PR, DI–PR and EN–DI–PR increases when the buffer capacity is increased. This is due to the fact when the buffer capacity is increased, more number of messages are stored in the node's buffer, thus more messages get delivered to the destination. It is also observed that the EN–DI–PR objectives yields the highest delivery probability (i.e. 0.53604) compared to that obtained when considering all other combinations of objectives. In terms of delivery probability, the EN–DI–PR objectives is 2.4% better than the EN–PR objectives, 5% better than the EN–DI objectives, and 15.32% better than the DI–PR objectives.

In Fig. 11, it is observed that among all combination of objectives, the EN–DI–PR objectives yields the lowest number of messages dropped (i.e. 46,852) as the buffer capacity is increased. In fact, the EN–DI–PR objectives

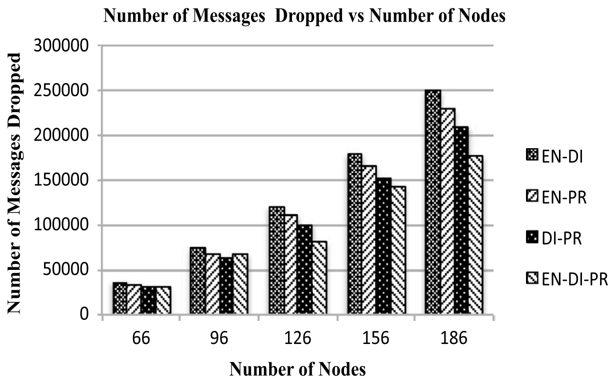

Fig. 7 Number of messages dropped vs. number of nodes

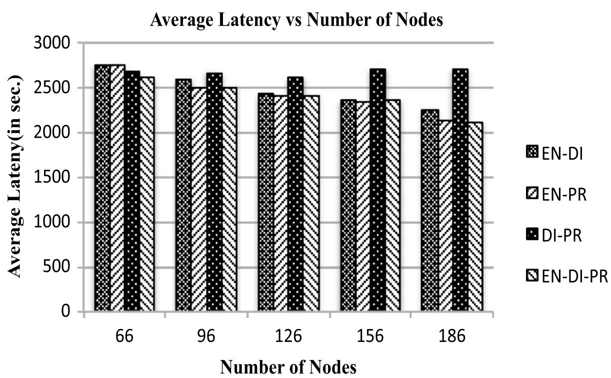

Fig. 8 Average latency (in s) vs. number of nodes

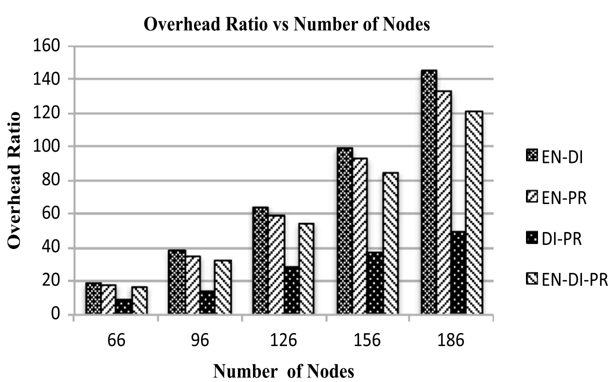

Fig. 9 Overhead ratio vs. number of nodes

is 25% better than the DI–PR objectives, 41% better than the EN–PR objectives, and 52.48% better than the EN–DI objectives.

In Fig. 12, it is observed that for the EN–DI, EN–PR and EN–DI–PR objectives, the average latency is increased when the buffer capacity is increased. In terms of average latency, the EN–DI–PR objectives is 1.86% better than the

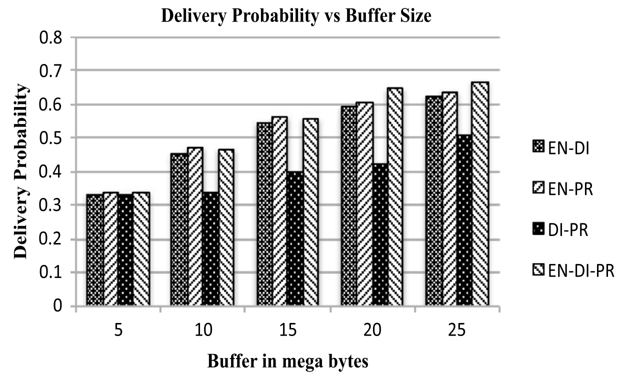

Fig. 10 Delivery probability vs. buffer size

EN–PR objectives, 5.03% better than the EN–DI objectives, and 12% better than the DI–PR objectives.

In Fig. 13, it is observed that the overhead ratio of EN–DI, EN–PR, DI–PR and EN–DI–PR decreases with an increase in the buffer size. It is observed that the DI–PR objectives generates the lowest overhead ratio compared to that generated when considering all other combinations of objectives. In addition, the EN–DI–PR objectives is 2.67% better than the EN–PR objectives, 5.21% better than the EN–DI objectives. Furthermore, the obtained standard deviation is 7.056 for the EN–DI–PR objectives, 5.8994 for the DI–PR objectives, 4.099 for the EN–PR objectives and 8.9207 for the EN–DI objectives.

Fifth, the performance of the MOTOR scheme in terms of delivery probability, messages dropped, average latency, and overhead ratio respectively, is evaluated using any of the above mentioned combinations of objectives (EN–DI, EN–PR, DI–PR and EN–DI–PR) under varying message generation interval. The results are captured in Figs. 14, 15, 16 and 17 respectively.

In Fig. 14, it is observed that the delivery probability of EN–DI, EN–PR, DI–PR and EN–DI–PR decreases when the message generation interval is increased. This is due to the lesser number of messages generated in the network when the message generation interval is increased, which in turn decreases the message dropping rate due to the increased buffer size of the nodes. It is also observed that the EN–DI–PR objectives yields the highest delivery probability (i.e. 0.65492) compared to that obtained when considering all other combinations of objectives. In terms of delivery probability, the EN–DI–PR objectives is 2.26% better than the EN–PR objectives, 3.64% better than the EN–DI objectives, and 51.27% better than the DI–PR objectives.

In Fig. 15, it is observed that the number of messages dropped using EN–DI, EN–PR, DI–PR, and EN–DI–PR decreases with an increase in the message

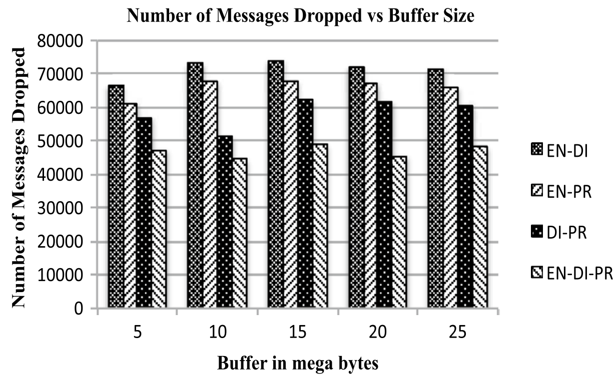

Fig. 11 Number of messages dropped vs. buffer size

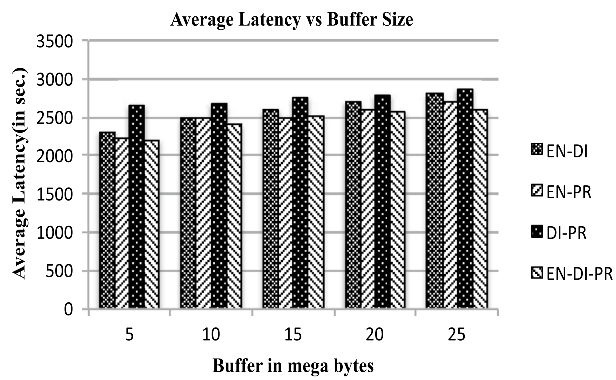

Fig. 12 Average latency (in s) vs. buffer size

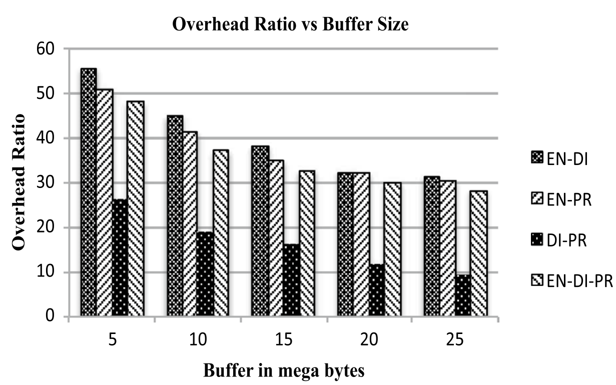

Fig. 13 Overhead ratio vs. buffer size

generation interval. This is due to the fact that a lesser number of messages is generated in the network when the message generation interval increases, which in turn decreases the message dropping rate. Among all combinations of objectives, the EN–DI–PR objectives yields the lowest number of messages dropped (i.e. 38,491) as the buffer capacity is increased. In fact, the EN–DI–PR objectives is 38.32% better than the DI–PR objectives, 53.3% better than

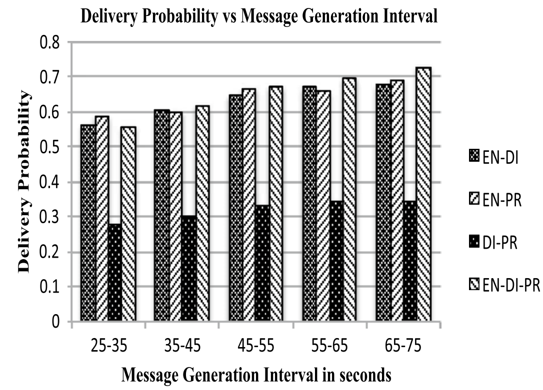

Fig. 14 Delivery probability vs. message generation Interval

the EN–PR objectives, and 68.35% better than the EN–DI objectives.

In Fig. 16, it is observed that for the EN–DI, EN–PR and EN–DI–PR objectives, the average latency is decreased when the message generation interval is increased. Among all combinations of objectives, the EN–DI–PR objectives yields the lowest average latency. In fact, in terms of average latency, the EN–DI–PR objectives is 2.08% better than the EN–PR objectives, 3.09% better than the EN–DI objectives, and 5.99% better than the DI–PR objectives.

In Fig. 17, it is observed that the DI–PR objectives generates the lowest overhead ratio compared to that generated when considering all other combinations of objectives. In addition, the EN–DI–PR objectives is 3.86% better than the EN–PR objectives, 6.79% better than the EN–DI objectives. Furthermore, the obtained standard deviation is 5.31 for the EN–DI–PR objectives, 6.1335 for the DI–PR objectives, 6.5141 for the EN–PR objectives, and 6.491 for the EN–DI objectives.

5 Conclusion

This paper has proposed a novel technique for optimized routing in OppNets (so-called MOTOR), which considers the node's context information such as number of encounters to destination (EN), distance to destination (DI), and delivery probability (PR), as routing decision patterns for selecting the best possible next hop candidate node to forward the data packets to destination, based on a combination of objectives, i.e. maximizing EN, maximizing PR, and minimizing DI. Simulation results have shown that using a combination of three objectives (EN–DI–PR) yields a better performance compared to that obtained when using a single objective or a combination of two objectives (EN–DI, EN–PR, or DI–PR)), in terms of average latency, number of messages dropped, and delivery probability. However, the proposed scheme does not perform well in

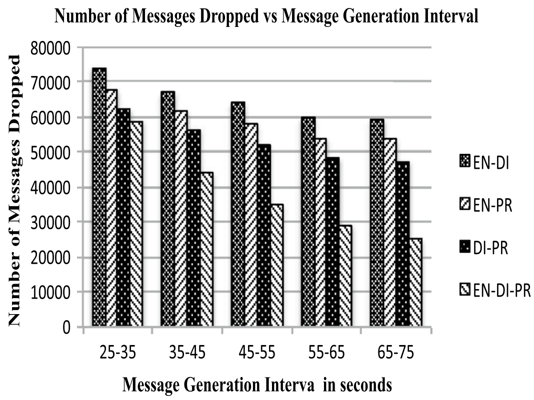

Fig. 15 Number of messages dropped vs. message generation Interval

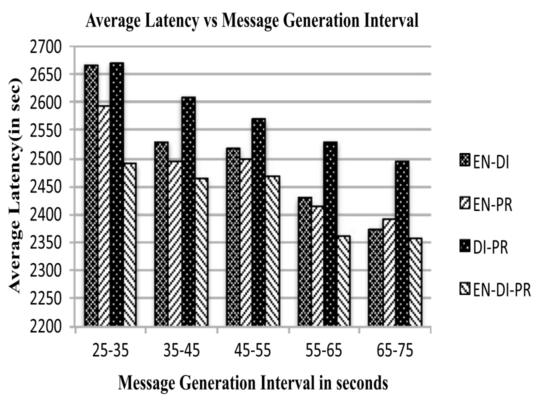

Fig. 16 Average latency (in s) vs. message generation interval

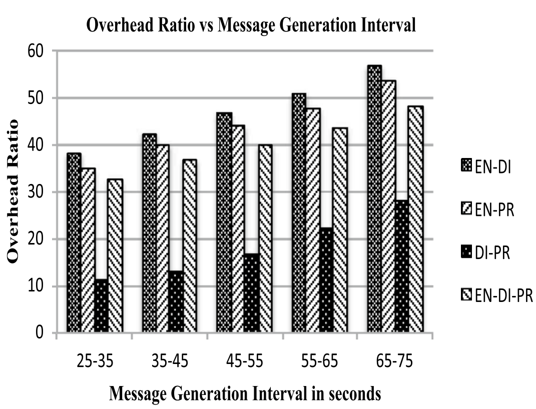

Fig. 17 Overhead ratio vs. message generation interval

terms of message overhead ratio. As future work, we intend to simulate the proposed scheme using various movement models. We also plan to incorporate energy and security as additional design constraints using the same multi-objectives target.

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